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Spatial heterogeneity of the relationship between vegetation dynamics and climate change and their driving forces at multiple time scales in Southwest China

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ABSTRACT

Under global climate change, relationship between vegetation dynamics and climate change is vital for vegetation conservation and restoration in fragile ecological system. However, the relationships at multiple time scales are unclear. Based on the Ensemble empirical mode decomposition method (EEMD), we revealed the spatial heterogeneity of vegetation dynamics and its relationship with climate change at multiple time scales in Southwest China during 1982–2015. Vegetation dynamics can be divided into 3-, 6-, 14-, and 32-year time scale oscillations with an increasing trend. Hereinto, the 3-year time scale and the increasing trend are dominant. In Guangxi and north of Guizhou provinces, vegetation dynamics was dominated by the long-term trend, whereas in the other areas it was dominated by the 3-year time scale. With increasing time scale, the impact of climate change became more pronounced. The relationship between vegetation dynamics and temperature in growing season was determined by elevation and vegetation type at the 3- and 6-year time scales, but only by vegetation type over the long-term trend. The relationship between vegetation dynamics and precipitation was driven by karst landform and vegetation type at the 3-year time scale, by precipitation amount at the 6-year time scale, and by karst landform and elevation over the long-term trend. Based on multivariate regression analysis with multiple time scale analysis, climate change had a good and significant interpretation on vegetation dynamics in 54.1% of the study area. Specifically, in Guangxi and north of Guizhou provinces, the impact of climate change on vegetation dynamics was greater than that of human activities. Our findings showed that multiple time scale analysis might facilitate a better understanding of the mechanisms of vegetation dynamics, and provide scientific knowledge on vegetation restoration and conservation in fragile ecosystems.

1. Introduction

Global warming and the associated increase in precipitation variability are major threats to terrestrial ecosystems (Jiménez et al., 2011; Craine et al., 2012; Miao et al., 2015). Vegetation is one of the most essential components of terrestrial ecosystems, due to its beneficial impacts on the terrestrial carbon balance and the climate system (Piao et al., 2011; Peng et al., 2012; Du et al., 2015; Hou et al., 2015; Tong et al., 2016a). Monitoring vegetation dynamics and its relationship with climate change is considered highly important for global change research and ecological environment conservation, since vegetation might be vulnerable and highly sensitive to climate change and external disturbances (Krishnaswamy et al., 2014; Sun et al., 2015; Tong et al., 2016a; Xie et al., 2016; Xu et al., 2016). The Normal Difference Vegetation Index (NDVI), which is strongly correlated with vegetation coverage, growth conditions, biomass and photosynthesis intensity, is widely used to monitor vegetation dynamics (Du et al., 2015; Sun et al., 2015; Tong et al., 2016b; Zhang et al., 2016a; Zewdie et al., 2017). A growing number of studies have used NDVI data to explore the relationship between vegetation and climate change (Wang et al., 2008; Yang et al., 2012; Sun et al., 2015; Tong et al., 2016b; Zewdie et al., 2017). However, most of them focused on single time scales using traditional time series analysis such as (partial) correlation analysis and linear regression models (Wang et al., 2008; Krishnaswamy et al., 2014; Du et al., 2015; Wang et al., 2015; Hou et al., 2015; Xie et al., 2016). The relationship between vegetation and climate variables is scale-

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dependent (Hawinkel et al., 2015; Liu and Menzel, 2016). Single time scale analysis cannot comprehensively reveal the response of vegetation to climate change, and may ignore some important information on other time scales. Recently, several studies focused on the relationships at multiple time scales (i.e. monthly, seasonally and annually, Wang et al., 2008; Yang et al., 2012; Tong et al., 2016b; Kong et al., 2017). However, these studies were mainly based on direct comparisons of different time series at different time scales, under linear and stationary assumptions (Hawinkel et al., 2015; Yin et al., 2016). In fact, the time series of NDVI and climatic variables, whatever monthly, seasonally or annually, are generally non-stationary and contain different frequency components, such as long- and short-term fluctuations (He et al., 2012; Verma and Dutta, 2012; Liu and Menzel, 2016; Yin et al., 2016). Therefore, a linear and stationary assumption is not optimal for exploring the relationship between vegetation and climate change. It is necessary to choose a suitable method to divide those non-stationary time series into variations at multiple time scales. Moreover, most studies focused on intra-annual time scales, and only few focused on inter-annual scales and long-term trends. The latter are considered to be crucial in understanding and predicting the response of ecosystems to an increasingly changing climate (Hawinkel et al., 2015). Therefore, it is essential to investigate the relationships between vegetation and climate change at multiple time scales, including annual, inter-annual, and inter-decadal scales, and long-term trends.

In addition to climate change, human activities are also the main driving forces of vegetation dynamics (Sun et al., 2015; Huang et al., 2016). With population expansion and economic development, human activities, such as urbanization, ecological management and restoration, overgrazing, and cropping, cause increasing influences on vegetation changes(Qu et al., 2015). To develop sustainable ways to cope with the consequences of climate change and economic development in fragile ecosystem, it is necessary to explore the relative importance of climate change and human activities on vegetation dynamics (Huang et al., 2016). A growing number of studies are thus differentiating between human-induced and climate-driven vegetation changes (Sun et al., 2015; Qu et al., 2015; Huang et al., 2016; Jiang et al., 2017; Li et al., 2017). The contributions of climate change and human activities are found to vary with spatial location, vegetation type, elevation, and time period (Wang et al., 2015; Huang et al., 2016; Jiang et al., 2017; Li et al., 2017). However, most studies quantify the relative role stemming from climatic variables at one single time scale under linear assumption. Ignoring the influences of climate change on vegetation dynamics at multiple time scale will underestimate the influences. Thus, multiple time scale analysis is necessary for assessing the relative importance of climate change and human activities.

The Ensemble Empirical Mode Decomposition (EEMD) method, which is advanced by Wu and Huang (2009), is thought to be a suitable time series processing tool to reveal the relationship between climate and vegetation at multiple time scales (Hawinkel et al., 2015; Yin et al., 2016). EEMD is an extension of the Empirical Mode Decomposition (EMD) methods (Huang et al., 1998). EEMD together with EMD can divide the non-stationary time series into a finite set of components with decreasing frequency and a residual trend component (Huang et al. 1998; Hawinkel et al., 2015). These are widely used in signal and image processing, climatic diagnosis, and hydrology (Wu and Huang, 2009; Hawinkel et al., 2015; Liu et al., 2016a; Chen et al., 2017). Recently, more studies have applied EEMD to remote sense data (Verma and Dutta, 2012; Hawinkel et al., 2015; Liu and Menzel, 2016; Yin et al., 2016; Wen et al., 2017). Although some identified the relationships between vegetation and climate variables at multiple time scales (Hawinkel et al., 2015; Liu and Menzel, 2016), they were not based on pixel scale, but rather in regional scale, which ignores spatial heterogeneity. The relationship has apparent spatial heterogeneity which are driven by different forces (Wang et al., 2008; Hou et al., 2015; Huang et al., 2016; Rishmawi et al., 2016; Tong et al., 2016a; Yin et al., 2016). Thus, multiple time scale analyses should be performed at the pixel scale to reveal the spatial heterogeneity of the relationships.

Southwest China is the most continuous karst region in China, with a high population pressure and underdeveloped economy (Wang et al., 2008; Li et al., 2016; Zhang et al., 2016b). It is one of the most fragile regions with low environmental capacity and poor self-recovery capability, and thus vulnerable to climate change (Peng et al., 2011; Jiang et al., 2014; Zhang et al., 2016b). Studying the relationship between vegetation dynamics and climate change in Southwest China may provide scientific knowledge for the protection of vegetation services and restoration of fragile ecological environments (Wang et al., 2008; Hou et al., 2015). Previous studies have already suggested this issue in this region (Wang et al., 2008; Hou et al., 2015; Tong et al., 2016a). However, the relationship at multiple time scales have not been studied yet.

In this paper, vegetation dynamics and climate change at multiple time scales were extracted using the EEMD method. Their relationships at multiple time scales were further explored to provide scientific knowledge for vegetation conservation and restoration in fragile ecosystems. For this, we aimed to: (1) Determine which time scale is dominantly responsible for vegetation dynamics. (2) Assess the spatial heterogeneity of the relationships between vegetation dynamics and climate change at different time scales and their driving forces. (3) Evaluate the relative importance of climate change and human activities on vegetation dynamics.

2. Materials and methods

2.1. Study area

Southwest China (97°38′E-112°10′E, 21°6′N -29°16′N), including Yunnan, Guizhou and Guangxi provinces, is located in the subtropical/tropical climate zone with annual precipitation > 1100 mm and average temperature > 20 °C (Fig. 1). The study area is dominated by karst landform and comprises about 384,343.38 km^2, occupying 48.32% of the total area of the three provinces.

2.2. Data sources

2.2.1. Normalized difference vegetation index (NDVI) dataset

The AVHRR NDVI3g (third generation, Pinzon and Tucker, 2014) dataset constructed by the Global Inventory Modelling and Mapping Studies (GIMMS) project for the period 1982–2015 was used in this study. This dataset, with the spatial resolution of 8 km and 15-day interval, has been widely used to monitor vegetation dynamics and reveal the relationship to climatic factors, due to its superior performance relative to prior versions and its capability for providing the longest time-series record from the early 1980s (Huang et al., 2016). The maximum-value composite (MVC) method was used to choose the higher value of bimonthly NDVI to obtain the monthly NDVI (Holben, 1986). To reflect the vegetation more appropriately, the NDVI products were averaged over the entire growing season from April to October to get growing-season NDVI (GSN).

2.2.2. Meteorology, DEM, karst and vegetation data

Monthly precipitation and temperature data during the period of 1957–2015 were collected by a network of approximately 120 weather stations provided by Climatic Data Center, National Meteorological Information Center, China Meteorological Administration (http://cdc.cma.gov.cn/). The growing-season summed precipitation (GSP) and growing-season mean temperature (GST) were then calculated here as the two main influencing climatic factors since they had a strong relationship with GSN. Based on DEM data (derived from United states geological Survey), these data were interpolated to continuous surface data with an 8 km spatial resolution to match NDVI dataset using thin-plate-smoothing spline-fitting techniques (Hutchinson, 1995) in ANUSPLIN 4.4 (http://fennerschool.anu.edu.au/research/products/

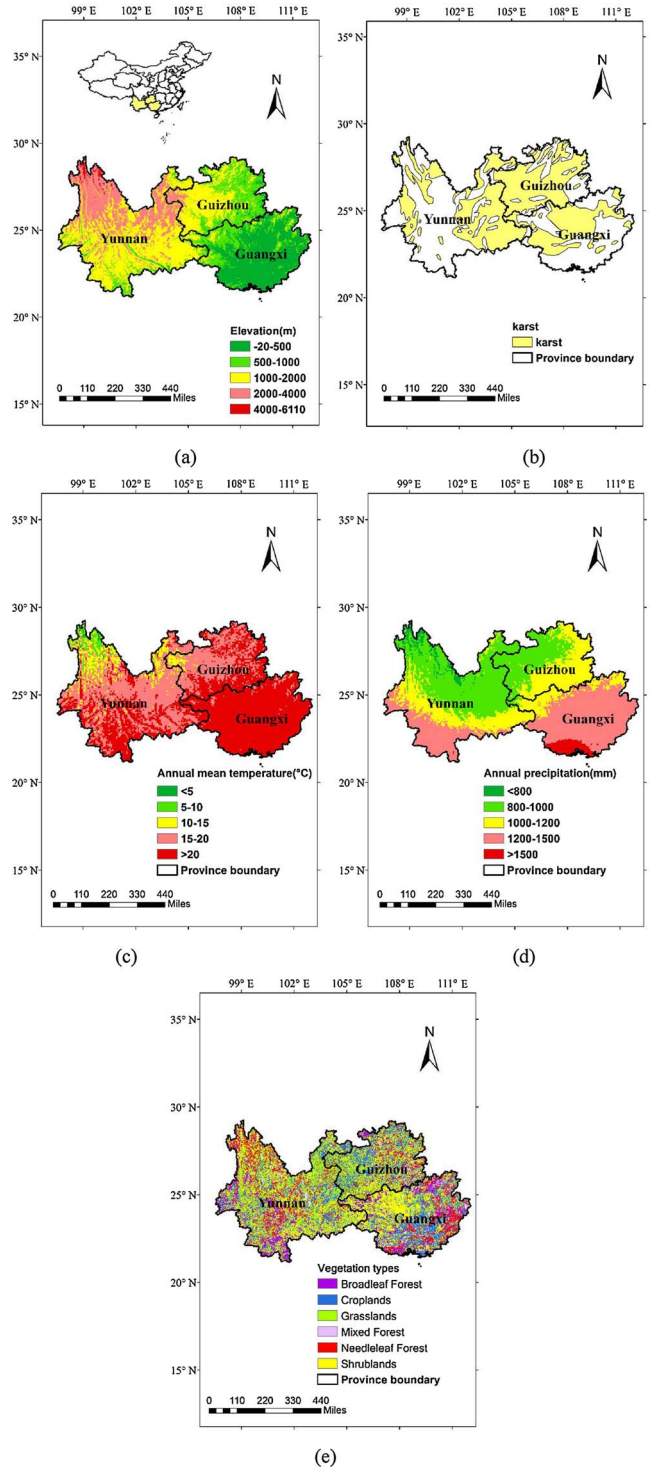


Fig. 1. Study area. (a) Elevation; (b) Karst area; (c) Annual Temperature; (d) Annual precipitation; (e) Vegetation types.

anusplin-vrsn-44).

The karst data in vector format were obtained from World Map of Carbonate Rock Outcrops v3.0 (http://web.env.auckland.ac.nz/our_research/karst/), and converted to raster data with 8 km spatial resolution in Arcgis 10.0 (ESRI, Inc., Redlands, CA, USA). Vegetation types were extracted from Multi-Source Integrated Chinese Land Cover Map (MICLCover2000, http://westdc.westgis.ac.cn/) with 1 km spatial resolution, and were resampled to 8 km spatial resolution to match NDVI dataset in Arcgis 10.0.

2.3. Ensemble empirical mode decomposition (EEMD)

EMD method is to decompose an original data sequence $X(t)(t = 1, 2, \ldots N, N$ is time length) into n components called as intrinsic mode functions (IMF_i, $i = 1, 2\ldots, n$) and a residue. The decomposition process (Huang et al., 1998; Liu et al., 2016a) can be described as follows:

Firstly, create the upper and lower envelopes of series $X(t)$ by connecting all local maxima and minima with cubic spline interpolation respectively. Then, the time series minus the means of upper and lower envelopes $m_1(t)$ to get the first component $g_1(t)$:

$$g_1(t) = X(t) - m_1(t) \tag{1}$$

$g_1(t)$ is not stationary, and thus the above process is repeated as:

$$g_{11}(t) = g_1(t) - m_{11}(t) \tag{2}$$

Where $m_{11}(t)$ is the mean of the envelopes of $g_1(t)$. The second subscript index indicates the additional repetition number for the sifting process.

The repeated process stopped when the following standard deviation (SD) is smaller than a pre-given value which was set as 0.2 in this paper.

$$SD = \sum_{t=1}^{N} [\frac{|g_{1k}(t) - g_{1(k-1)}(t)|^2}{g^2_{1(k-1)}(t)}] \tag{3}$$

and

$$g_{1k}(t) = g_{1(k-1)}(t) - m_{1k}(t) \tag{4}$$

Where k is the number of iterations respectively.

So, the first IMF component ($c_1 = g_{1k}(t)$) is extracted from the data, and then the rest of the data is

$$r_1 = X(t) - c_1 \tag{5}$$

Because r_1 still contains oscillations of longer period, the same sifting process described above is repeated and the subsequent r_i can be described as:

$$r_i = r_{i-1} - c_i,\ i = 2, 3\cdots n \tag{6}$$

$$\text{i.e., } X(t) = \sum_{i=1}^{n} c_i + r_n \tag{7}$$

where c_i is the ith IMF component, and r_n is the residue.

The sifting process will stop when the residue r_n becomes a monotonic function, or contains at most one extreme (Huang et al., 1998). Thus, a finite number of IMFs with decreasing frequency and a residue trend r_n were extracted from the original time series according to the intrinsic characteristic of the sequence itself.

However, for EMD, there is a problem caused by mode mixing which can result in an overestimation of the noise in the signal (Wu and Huang, 2009). Therefore, the ensemble EMD (EEMD) method was advanced by adding white noise to the original series as follows (Wu and Huang, 2009):

Firstly, add a number (l) of Gaussian white noise $P_j(t)$ to the original signal $X(t)$ to obtain a number of noisy pseudo signals $X_j(t)$.

$$X_j(t) = X(t) + P_j(t),\ j = 1, 2, \ldots l \tag{8}$$

l is adopted as 1000 in this paper.

Secondly, apply EMD method to these noisy pseudo signals $X_j(t)$.

Finally, the ith EEMD IMFs $c_i(t)$ and r_n are obtained by averaging the corresponding EMD IMFs and residue of these noisy pseudo signals as the following:

$$c_i(t) = \frac{1}{l}\sum_{j=1}^{l} c_{ij}(t) \text{ and } r_n = \frac{1}{l}\sum_{j=1}^{l} r_{nj}(t) \tag{9}$$

Where c_{ij} and r_{nj} denotes the ith IMF and r_n from $X_j(t)$.

Thus, EEMD produces a finite number of IMFs and a residue r_n. Each IMF component represents the oscillation of the original time series at

one time scale. The residue reflects the long-term trend of the original sequence.

The mean period of the *i*th IMF component can be obtained by counting the number of its peaks (local maxima) and then being divided by the time length (*N*). The variance contributions were figured out to assess the relative importance of each IMF component and the residue as the following:

$$Vc_i = Var(c_i)/[\sum_{i=1}^{n} Var(c_i) + Var(r_n)] \quad (10)$$

and

$$Vr_n = Var(r_n)/[\sum_{i=1}^{n} Var(c_i) + Var(r_n)] \quad (11)$$

Where Vc_i and Vr_n are the variance contributions of the *i*th IMF component and residue (r_n) respectively. $Var(c_i)$ and $Var(r_n)$ are the variance of the *i*th IMF component and residue(r_n).

2.4. Relative importance of climate changes and human activities for NDVI based on multivariate regression analysis

To completely and deeply understand the relationship between NDVI and climate change, we conducted multivariate regression analysis. The adj-R^2 is usually interpreted as the percentage of the total variation of the dependent variable (e.g. NDVI) that can be explained by all independent variables (e.g. temperature and precipitation) adjusted for the number of variables used (Xu et al., 2003; Wen et al., 2017). The significance of the adj-R^2 was estimated by an F-test at a significance level of 0.05.

Firstly, we defined GSN as the dependent variable and GST and GSP as independent variables to build the standardization of multivariate linear regression without multiple time scale analysis, and then, we calculated the adjusted multiple coefficient of determination (adj-R_n^2).

Secondly, we defined GSN as the dependent variable, and GST and GSP at different time scales (all IMFs and residues) as independent variables to build multivariate linear regression with multiple time scale analysis, and then calculated the adjusted multiple coefficient of determination (adj-R_m^2).

Thirdly, adj-R_n^2 and adj-R_m^2 were compared to reveal the improvement in the interpretation of climate changes on NDVI with multiple time scale analysis.

Finally, the adj-R_m^2 with multiple time scale analysis is used as the percentage of the total influence of climate changes on NDVI. The remaining fraction (i.e., one minus adj-R^2) was then used to evaluate the effects of human activities on NDVI variations, at least preliminarily. So, the adj-R_m^2 and the remaining fraction were used to evaluate the relative importance of climate change and human activities for vegetation dynamics.

3. Results

3.1. Multiple time scale analysis for vegetation dynamics

To explore the spatial heterogeneity of vegetation dynamics at different time scales in Southwest China, multiple time scale analysis for GSN was performed on the pixel scale during 1982–2015 using EEMD. Fig. 2 and Table 1 show the temporal changes in GSN and the average periods with their respective variance contributions at different time scales. Values were averaged on all pixels.

GSN can be divided into four IMF components and a residue (Fig. 2 and Table 1). IMF1 showed the greatest variance contribution, followed by IMF2. The contributions of IMF3 and IMF4 were very small (7.4 and 2.2% respectively), and thus were not considered in the following analyses. The residue showed an increasing trend, with 32.0% variance contribution, which is smaller than that of the 3-year time scale

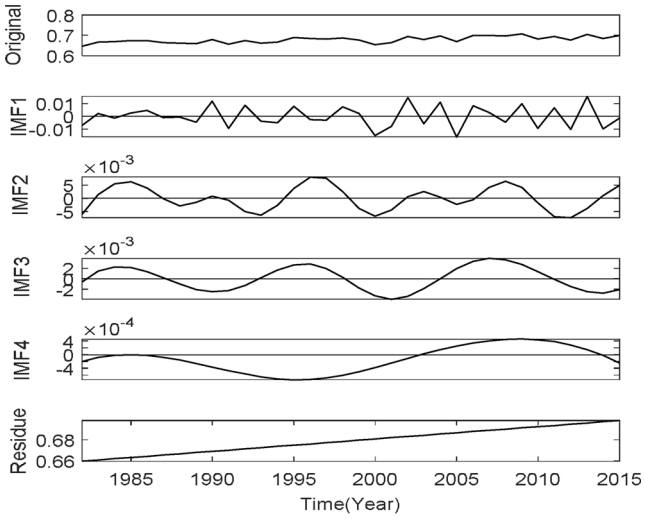


Fig. 2. Average temporal changes in growing-season NDVI (GSN) during 1982–2015 at different time scales and the pixel scale based on the EEMD method.

Table 1
Average periods and their respective variance contributions of growing-season NDVI (GSN) changes at different time scales in Southwest China on the pixel scale.

	IMF1	IMF2	IMF3	IMF4	Residue
Period (year)	3	6	14	32	–
Variance contribution (%)	42.9	15.5	7.4	2.2	32.0

(42.9%), but much larger than the others. Therefore, the results suggest that vegetation dynamics in Southwest China was mostly characterized by 3-year oscillations and an increasing trend. Variance contributions of 3- and 6-year oscillations, and the long-term trend of NDVI changes showed a strong spatial heterogeneity (Fig. 3).

For the 3-year time scale, the variance contribution was below 40% in the north of Yunnan Province, which is dominated by needleleaf forests. This is same for most parts of Guangxi and north of Guizhou provinces, which have favorable climate conditions and low elevations, and are dominated by croplands, needleleaf forests and shrublands (Fig. 3a). Therefore, the 3-year oscillations of vegetation in these areas were small. In contrast, variation contribution was larger (between 40–60%) in northwest and south of Yunnan Province, south of Guizhou Province, and northeast of Guangxi Province. These areas are mainly dominated by broadleaf and mixed forests with elevations between 2000–4000 m.

For the 6-year time scale, variation contribution was above 15.5% in Yunnan Province, while it was below 10.0% in Guizhou and Guangxi provinces (Fig. 3b). The elevation in Yunnan Province is > 2000 m, and much higher than in the other two provinces. Climate conditions are also much harsher. Therefore, vegetation dynamics was more sensitive to short-term external disturbances, and the oscillations of short time scales were more significant in Yunnan Province.

Over long-term trends, variation contributions in most parts of Guangxi and north of Guizhou provinces were much greater, ranging from 50 to 90% (Fig. 3c), opposite to 3-year time scale oscillations. It suggests that these areas were dominated by long-term trends. These areas are dominated by croplands, needleleaf forests and shrublands, with low elevation and mild climate conditions; therefore, the long-term changes in vegetation were much greater than the short-term changes. In most parts of Yunnan and the border between Guangxi and Guizhou provinces, the variance contribution of long-term changes was < 40%, much smaller than that of 3-year oscillations. Therefore, in these areas, vegetation dynamics was dominated by 3-year time scale oscillations.

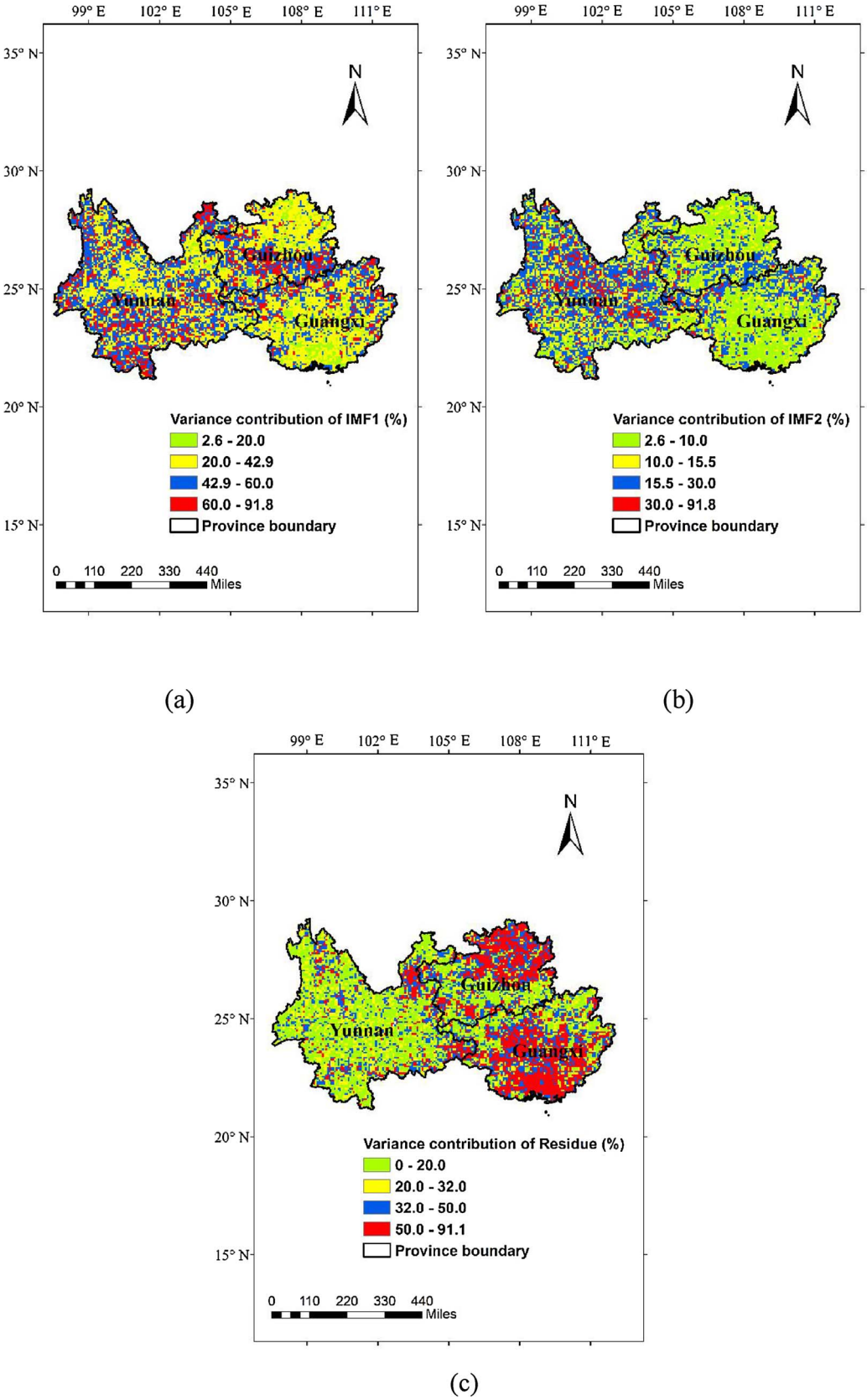
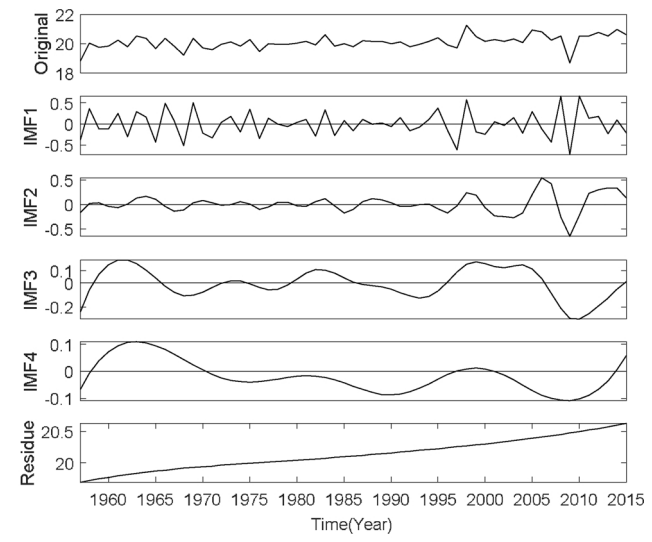


Fig. 3. Spatial distribution of variance contributions of NDVI oscillations at 3-year (a), 6-year (b) time scales and the long-term trend (c).

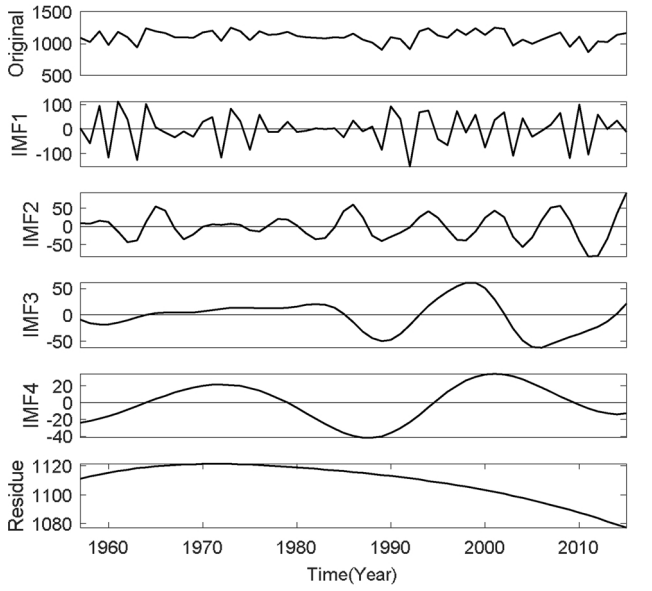
For croplands, the variance contribution of 3-year oscillations was close to that of the long-term trend, and much smaller than the average value of 42.9% (Table 2). It suggests that cropland was dominated by both 3-year time scale and long-term trend. Probably this could be attributed to the fact that croplands are planned by human activities with small oscillations. For the other vegetation types, the variance

Table 2
Variance contributions for different vegetation types at different time scales (%).

	Broadleaf forest	Mixed forest	Needleleaf forest	Shrublands	Grassland	Cropland
IMF1	46.3	45.0	42.7	43.1	43.8	40.3
IMF2	16.2	15.3	15.7	15.4	16.5	14.2
Residue	27.2	30.2	31.8	32.1	29.6	36.1



(a)



(b)

Fig. 4. Temporal changes of growing-season temperature (a) and precipitation (b) changes at different time scales based on EEMD in Southwest China during 1957–2015.

contribution of 3-year oscillations was much larger than that of 6-year oscillations and long-term changes, especially for broadleaf and mixed forests (Table 2). Therefore, broadleaf and mixed forests were dominated by 3-year time scale oscillations.

Table 3
The average periods and their variance contributions of growing-season temperature (GST) and precipitation (GSP) changes at different time scales in Southwest China during 1957–2015.

		IMF1	IMF2	IMF3	IMF4	Residue
GST	Period (year)	3	6	12	24	–
	Variance contribution (%)	41.9	21.1	11.1	4.2	21.7
	Rank	1	3	4	5	2
GSP	Period (year)	3	6	13	30	–
	Variance contribution (%)	57.0	21.5	11.8	5.3	4.4
	Rank	1	2	3	4	5

3.2. Relationship between vegetation dynamics and climate change at multiple time scales

3.2.1. Multiple time scale analysis for climate change

To reveal the changes in GST and GSP at different time scales, multiple time scale analysis was performed using EEMD at the pixel scale during 1957–2015. Fig. 4 and Table 3 indicate the temporal changes, and the average periods and their variance contributions of GST and GSP at different time scales. Values were averaged for all pixels.

GST changes in Southwest China showed four oscillations at 3-, 6-, 12-, and 24-year time scales, among which the 3-year oscillations were the greatest (Fig. 4a and Table 3). In addition, for the long-term trend, the average GST increased rapidly and then gradually, with variance contribution smaller than the 3-year oscillation. GSP changes in Southwest China had four oscillations of 3-, 6-, 13-, and 30-year time scales, among which 3-year oscillations was by far larger than the others (Fig. 4b and Table 3). The long-term trend of GSP increased before the 1970s and then decreased gradually with the lowest variance contribution. Thus, the GSP in southwest China was mainly dominated by the 3-year time scale, with an insignificantly small decreasing trend as a whole.

3.2.2. Possible relationships between NDVI and climate change at different time scales

To reveal possible relationships between NDVI and climate change at different time scales, Pearson correlation analysis was performed for each pixel for GSN and concurrent climatic factors (GST and GSP) at different time scales during 1982–2015 (Figs. 5–7). In addition, the percentage areas for different types of relationships among GSN, GST, and GSP at different time scales are shown in Table 4.

For the 3-year time scale, vegetation dynamics had a negative relationship with temperature in 64.37% of the total study area, especially for the Yunnan Province (Fig. 5a and Table 4). In Guizhou and most parts of the Guangxi provinces (35.38%), NDVI showed a positive relationship with temperature, except for needleleaf and broadleaf forests. The relationship between NDVI and precipitation in the growing season was negative for most study area, especially in karst regions with high elevation (Fig. 5b). The significantly negative relationship ($p < 0.1$) found in 12.30% of the area, was mainly located in marginal areas of the three provinces, which were grassland-dominated. Positive relationships were mainly found in non-karst areas and karst areas in the Guangxi Province that have low elevation and mild climate conditions. This indicates that increasing precipitation might promote vegetation growth.

For the 6-year time scale, the relationship between NDVI and temperature was negative in most areas of Yunnan Province, especially for the needleleaf forest showed a significantly negative relationship (Fig. 6a). However, in southwest of Yunnan Province, the relationship was positive. In Guangxi and Guizhou provinces, the area with positive relationship increased considerably. Moreover, the relationship was significantly positive in the areas dominated by shrublands and croplands. The relationship between NDVI and precipitation was mainly

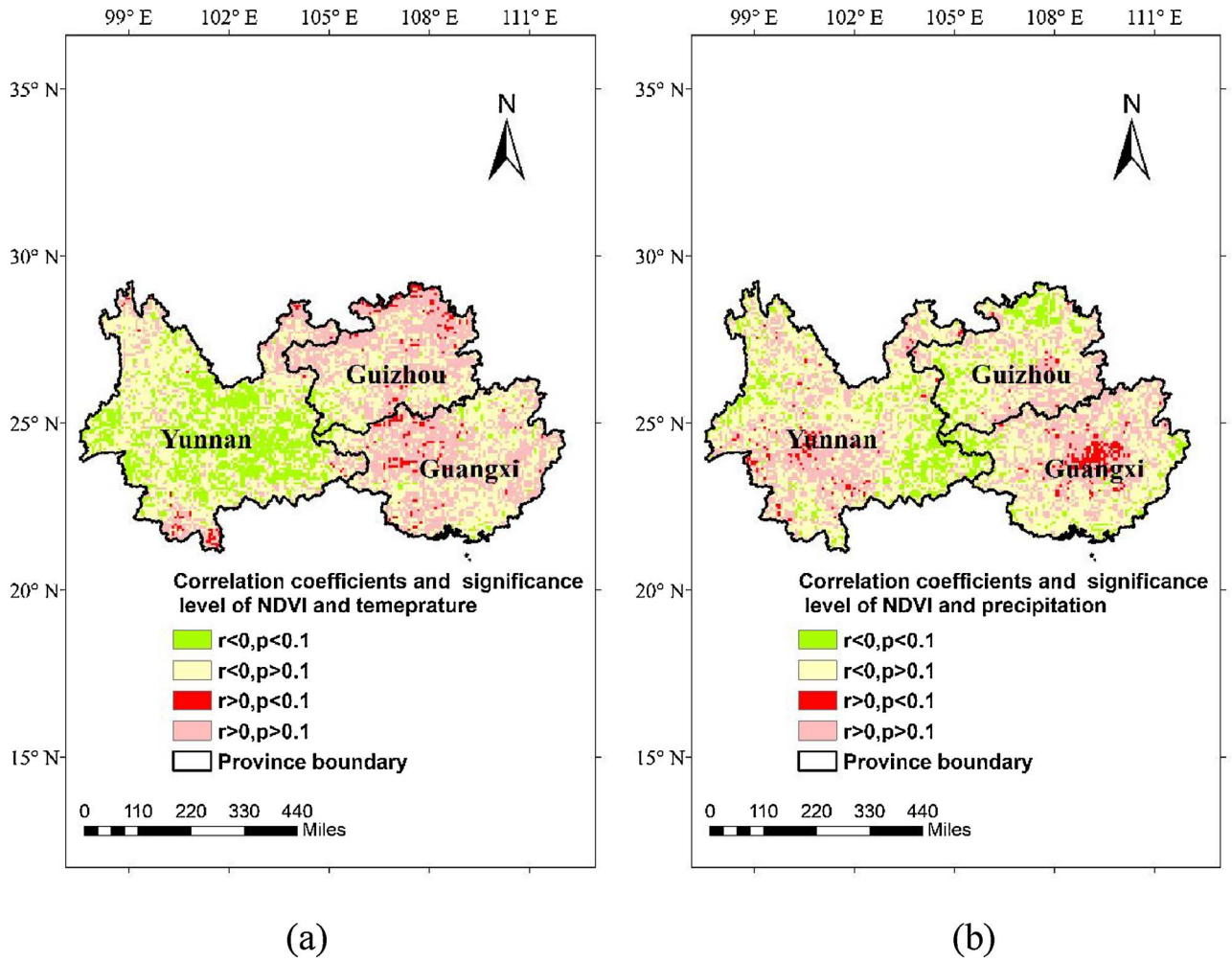


Fig. 5. Relationship between GSN and GST (a) and GSP (b) at 3-year time scale in Southwest China (*r*: correlation coefficient; *p*: significance level).

negative in Yunnan and Guizhou provinces, whereas it was positive in Guangxi Province (Fig. 6).

Over the long-term trend, NDVI had a significantly positive relationship with temperature in most Southwest China, except for the north and east of Yunnan Province, which is dominated by needleleaf forests (Fig. 7a). Therefore, long-term temperature increasing will not favor needleleaf forests. NDVI showed a significantly positive relationship with precipitation in the north of Yunnan and in the middle of Guangxi provinces (Fig. 7b), probably due to long-term increasing precipitation, which favored vegetation growth. However, NDVI had a significantly negative relationship in most karst area, except for the karst area in Guangxi Province with low elevation and mild climate.

With the increase in time scales, the area with significantly positive relationship between NDVI and temperature increased strongly (Table 4). Particularly, 75.63% of the areas showed significantly positive relationship for long-term trends. As the time scale increased, the significance of the relationship between NDVI and precipitation increased with the area percentage increasing from 14.99 to 90.13%. However, the relationship was first negative, then positive, and finally negative.

3.3. Relative importance of climate change and human activities to vegetation dynamics in Southwest China

To reveal the relative importance of climate change and human activities for NDVI, we conducted a multivariate regression analysis for NDVI based on the annual GST and GSP, with and without multiple time scale. Fig. 8 shows the spatial distribution of the adjusted-R^2 (adj-R^2) and the significance of multivariate regression analysis without and with multiple time scale analysis.

For regressions without multiple time scale analysis, only 8.54% of the areas passed the significance test ($p < 0.05$) with very low adj-R^2 (average value = 0.19), indicating that climate change imposes minimal impact on NDVI in most study areas (Fig. 8a). However, for regressions accounting for multiple time scales, 54.10% of the areas showed significance with an average adj-R^2 of 0.48 (Fig. 8b). It suggests that climate change indeed significantly affects NDVI, which was close to those from human activities in most study area. Thus, ignoring time scales may strikingly underestimates the impact of climate change on vegetation dynamics. Furthermore, 21.98% of the areas passed significance test ($p < 0.05$) with adj-R^2 greater than 0.5. These areas were mainly located in Guangxi and north of Guizhou provinces. It indicates that the impact of climate change on NDVI was greater than that of human activities, because of mild climate conditions and low elevation. In the north and east of Yunnan Province, but also in the border between Yunnan and Guizhou provinces, which are dominated by needleleaf forests and grasslands, adj-R^2 was < 0.5 but significant ($p < 0.05$). It suggests that climate change significantly affects NDVI, but less than human activities. In the north of Guizhou and Guangxi provinces, and southwest of Yunnan Province, which are dominated by the 3-year NDVI oscillations, adj-R^2 was lower than 0.5 without significance. The 3-year oscillations were hardly related to temperature and precipitation. Therefore, the results suggest that these areas were impacted by human activities, but not by climate change.

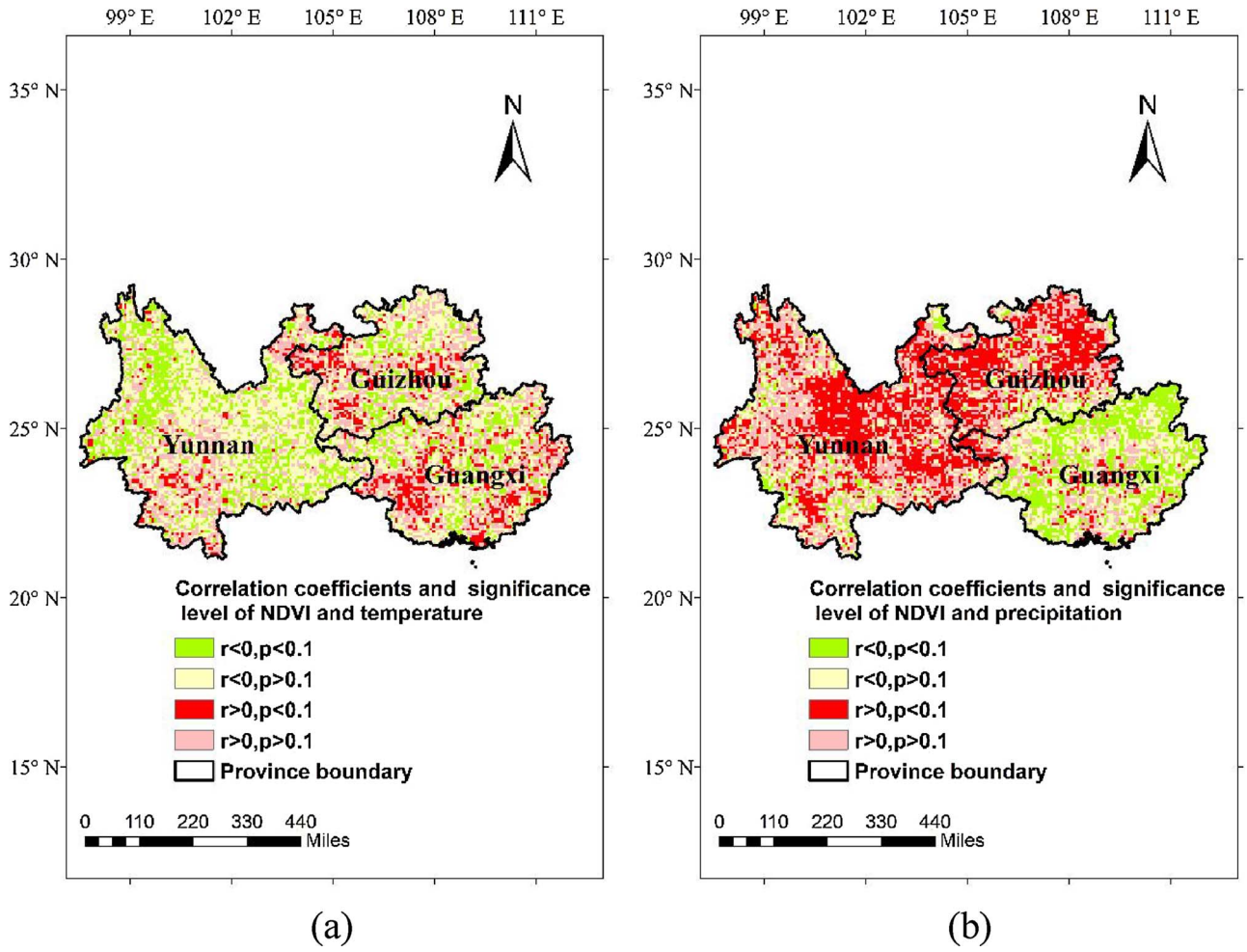


Fig. 6. Relationship between GSN and GST (a) and GSP (b) at 6-year time scale in Southwest China (*r*: correlation coefficient; *p*: significance level).

4. Discussion

4.1. Vegetation dynamics at different time scales in Southwest China

Using the EEMD method, vegetation dynamics could be divided into oscillations at 3-, 6-, 14-, 32-year time scales and an increasing trend. The variance contributions of the oscillations at 3-year time scales and long-term trend were by far larger than the others. Therefore, vegetation dynamics was dominated by 3-year time scale and long-term trend. The dominance of oscillations of different time scales showed obvious spatial heterogeneity. In Guangxi and north of Guizhou provinces, the variance contribution of the long-term trend was greater than that of the 3-year time scale. Thus, vegetation dynamics was characterized not by short time scales, but by the long-term trend. In other areas, the variance contribution of the 3-year time scale was much greater than that of the long-term trend, and thus characterized by the 3-year time scale. For broadleaf and mixed forests, the variance contribution of the 3-year time scale was much greater than that of the long-term trend, and thus vegetation dynamics was dominated by the 3-year time scale. However, for croplands, the contribution of the 3-year time scale was similar to that of the long-term trend, indicating that croplands were characterized by both 3-year oscillations and the long-term trend.

4.2. Relationships between NDVI and climate change at multiple time scales and their driving forces

Previous studies consider the relationship between vegetation and temperature as mainly positive, and the relationship to precipitation as weak in Southwest China (Wang et al., 2008; Hou et al., 2015). Moreover, spatial heterogeneity of the relationships was thought to be driven by the spatial variation in climate conditions and complex karst landforms (Hou et al., 2015). However, our study found that the relationships between vegetation and climate change varies with the time scale, which was mainly determined by vegetation type, karst landform, topography and climatic condition.

At the 3-year time scale, most study areas showed no significant relationship between NDVI and climate change. Significant relationships occurred in approximately 20% of the areas. The relationship between growing-season NDVI and temperature was mainly influenced by elevation and vegetation type. Nearly 50% of the areas showed a negative relationship, mainly located in Yunnan Province, with elevation > 1500 m. The positive relationship mainly existed in croplands and shrublands in Guangxi and Guizhou provinces, where elevation is < 1000 m, with favorable climatic conditions. The relationship between NDVI and precipitation in growing season was influenced by karst landform and vegetation type. The relationship was negative in most study area, mainly distributed in karst regions. Karst areas have low water-soil retaining ability (Jiang et al., 2014; Liu et al., 2016b), and thus short-term precipitation increase may cause serious water and soil losses, further preventing plant growth. More specifically, the significantly negative relationship can be found in the border between the three provinces, dominated by grasslands. The grass roots are generally short and cannot protect soil and water from being lost by the increasing precipitation at short timescales. In contrast, the positive relationship is mainly located in non-karst area, and karst area with low elevation in Guangxi Province. In non-karst areas, increasing

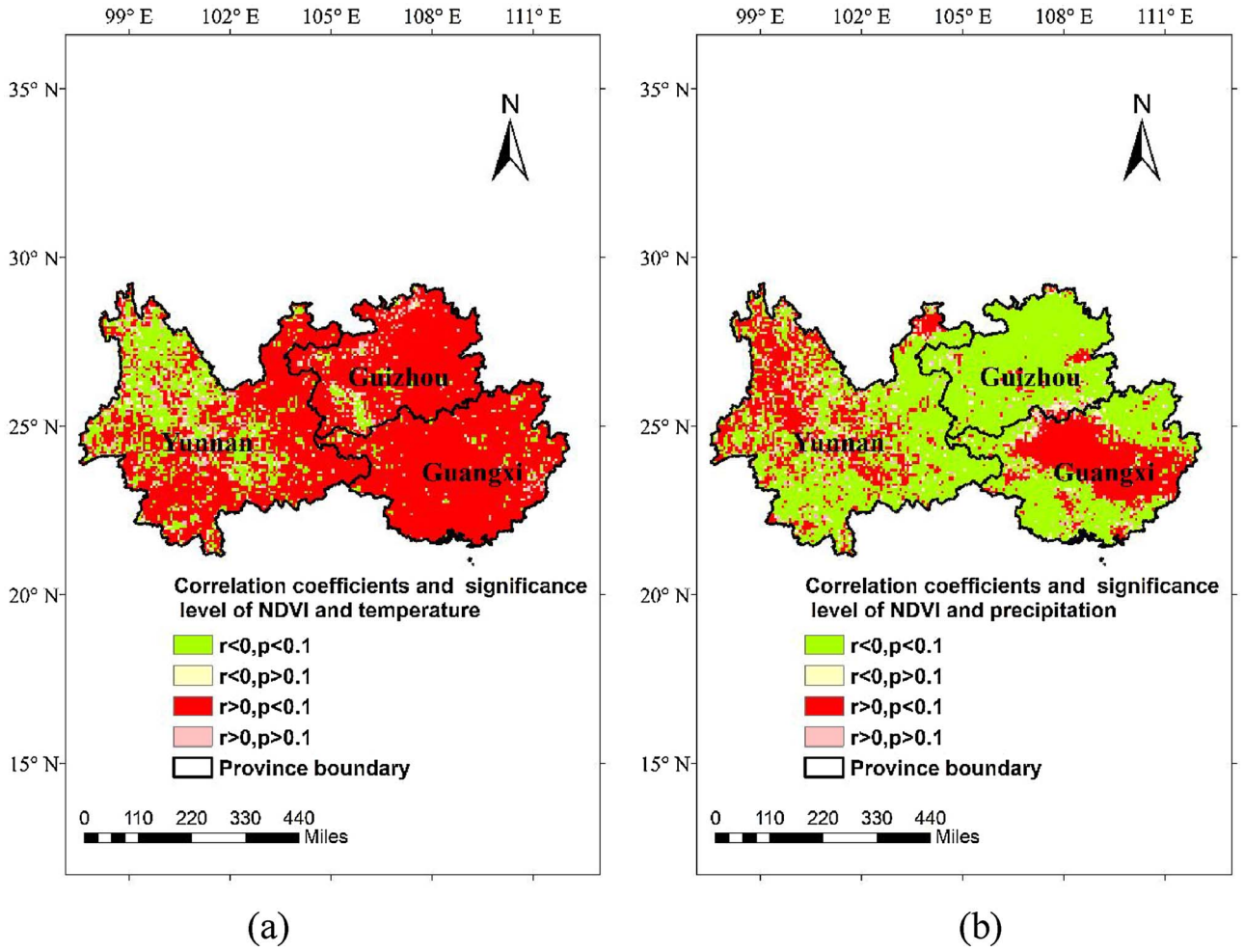


Fig. 7. Relationship between GSN and GST (a) and GSP (b) over long-term trend in Southwest China (*r*: correlation coefficient; *p*: significance level).

Table 4
Area percentages for different types of relationships between GSN and climate (GST and GSP) at different time scales.

	IMF1		IMF2		Residue	
	GST	GSP	GST	GSP	GST	GSP
$r > 0, p < 0.1$	2.36	2.69	10.77	30.28	75.63	28.45
$r > 0, p > 0.1$	33.02	31.12	28.77	31.48	4.45	4.89
$r < 0, p < 0.1$	16.75	12.30	20.07	14.75	16.08	61.68
$r < 0, p > 0.1$	47.87	53.89	40.39	23.50	3.84	4.99

precipitation can promote vegetation growth by enhancing soil moisture. In karst areas with low elevation, increasing precipitation cannot prevent, but instead promote vegetation growth, because low elevation is less prone to cause water and soil loss.

For the 6-year time scale, the relationship between NDVI and temperature was still negative in most study area. The significant negative relationship mainly occurred in the needleleaf forest of Yunnan Province. The areas with a significantly positive relationship increased considerably, especially for those dominated by shrublands and croplands. The relationship between NDVI and precipitation was mainly driven by precipitation abundance. In Guangxi Province, there is a large amount of precipitation (> 1400 mm); hence, increasing precipitation might prevent plant growth. In contrast, in Yunnan and Guizhou provinces, precipitation is much lower than 1000 mm; thus, increasing precipitation will promote plant growth.

For the long-term trend, the relationship between NDVI and temperature was mainly affected by the vegetation type. In the north and east of the Yunnan province, increasing temperature was unfavorable for the growth of needleleaf forests. For the other vegetation types, increasing temperature might favor vegetation growth. The relationship between NDVI and precipitation was mainly affected by karst landform and elevation, and it was negative for most study areas, except for the north of Yunnan province, and the middle of Guangxi province. In karst area with high elevation, long-term precipitation increase will inhibit plant growth, whereas in non-karst area and karst areas with low elevation, long-term precipitation will promote vegetation growth.

Wang et al. (2008) reported that NDVI had no significant correlations with temperature and precipitation in most study areas considered here. However, in our study, only for the 3-year time scale were found for most regions insignificant relationships. With the increasing of the time scale, the area with a significantly positive relationship between NDVI and temperature increased remarkably. Particularly, 75.63% of the total area showed a significant positive relationship for the long-term trend. Similarly, the area with significant relationship between NDVI and precipitation increased from 14.99% to 90.13%, and the relationship changed from negative to positive, but finally to negative. These demonstrated that the impact of climate change on NDVI became more pronounced with the increasing of the time scale, especially for long-term trends.

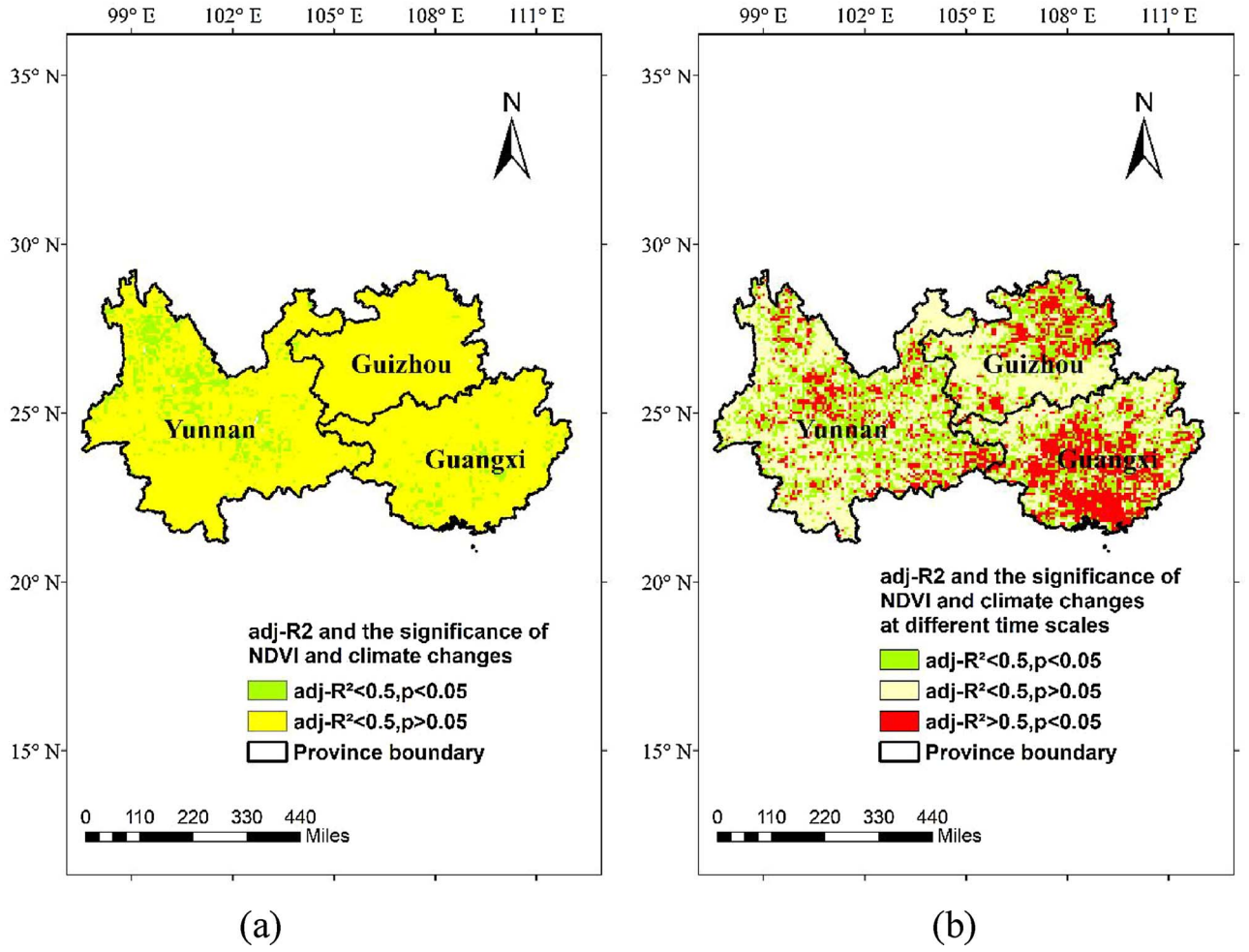


Fig. 8. Spatial distribution of adjusted-R^2 and its respective significance for (a) multivariate regression analysis (without multiple time scale analysis) of NDVI based on temperatures and precipitation during growing season, and (b) multivariate regression analysis (with multiple time scale analysis) of NDVI on temperature and precipitation during growing season at four time scales with the long-term trend (IMFs 1–4 and residue).

4.3. Relative importance of climate change and human activities for vegetation dynamics

Previous studies pointed out that the determination coefficients of both GST and GSP were low based on multivariate regression analysis, without multiple time scale analysis, which indicates a limited influence on NDVI (Hou et al., 2015; Tong et al., 2016a). However, using multivariate regression analysis for NDVI based on temperature and precipitation at different time scales by the EEMD method in our study, we found an average adj-R^2 in 54.1% of our study area of 0.48. This demonstrates that the impact of climate change may be very close to that of human activities. In particular, for Guangxi and north of Guizhou provinces, the impact of climate change was even greater than that of human activities.

4.4. Implication for vegetation conservation and restoration

Although NDVI showed a significant increase as a whole in Southwest China, only in Guangxi and north of Guizhou provinces, with mild climatic conditions, vegetation dynamics was dominated by the long-term trend. In karst areas with high elevation, vegetation dynamics was dominated by short-time oscillations, which suggest that fragile ecosystems are more unstable. Short-term human activities cannot cause long-term impacts on vegetation. Thus, long-term reforestation and deforestation are required for long-term vegetation increase.

For growing-season temperatures, the residue extracted by EEMD showed an obviously increasing trend, which was consistent with the results of Hou et al. (2015) and Liu et al. (2015). Long-term temperature increase may favor plant growth, except for needleleaf forest, and thus may provide chances for vegetation regrowth. However, temperature increase may prevent the growth of needleleaf forests. Therefore, in the future, more attention should be paid on the conservation of needleleaf forests. Moreover, preferentially shrubs should be used instead of conifers for reforestation, because the former are favored by increasing temperatures.

In Southwest China, topography is highly complex, especially within the largest continuous karst area (Li et al., 2016). The topography affects the relationships between NDVI and temperature at short time scales. Temperature increasing at short time scales will prevent vegetation growth in high-altitude areas. Therefore, attention should be paid on temperature increasing at short time scales to avoid the degradation of fragile ecological environments in high-altitude areas, especially for Yunnan Province. Previous studies considered NDVI as weakly negatively related to the growing-season precipitation, due to abundant precipitation (Wang et al., 2008, 2015; Hou et al., 2015; Tong et al., 2016a). However, only for the 6-year time scale, will the precipitation amount affect the relationship between NDVI and precipitation. For the 3-year time scale and long-term trend, the relationship was affected by both karst landforms and topography. In karst areas with high elevation, precipitation increasing should prevent vegetation growth for both short time scale and long-term trend. EEMD analysis

showed that the growing-season precipitation in Southwest China was dominated by short time scale oscillations with a slightly decreasing trend, in accordance with Hou et al (2015). Therefore, water and soil conservation is important for vegetation restoration at short time scales.

5. Conclusion

Multiple time scale analysis for the relationship between vegetation dynamics and climate change was performed with the EEMD method. Vegetation dynamics was dominated by the 3-year time scale and long-term trend, with apparent spatial heterogeneity. In Guangxi and north of Guizhou provinces, vegetation dynamics was dominated by the long-term trend. In the other areas, it was dominated by the 3-year time scale. As the time scale increased, more areas showed significant relationships between NDVI and climatic factors (temperature and precipitation). The relationships between vegetation dynamics and climate change at different time scales showed clear spatial heterogeneity patterns. The relationships between vegetation dynamics and temperature were determined by elevation and vegetation type at 3- and 6-year time scales, but only by vegetation type for the long-term trend. The relationship between vegetation dynamics and precipitation was driven by karst landforms and vegetation type at the 3-year time scale, by precipitation amount at the 6-year time scale, and by karst landform and elevation for the long-term trend. Multivariate regression analysis with multiple time scale analysis showed that climate change had a deep impact on vegetation dynamics in most study areas. Specifically, in Guangxi and north of Guizhou provinces, the impact of climate change was greater than that of human activities. The findings of this study facilitate better understanding of the relationships between vegetation dynamics and climate change at multiple time scales, and also provide some scientific references for vegetation conservation and restoration for fragile ecosystems under global climate change.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.agrformet.2018.02.015.

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